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CARBON-AWARE KUBERNETES SCHEDULING FOR ENERGY-EFFICIENT CLOUD-NATIVE COMPUTING ENVIRONMENTS

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ABSTRACT

The rapid expansion of cloud-native computing, containerized applications, microservices, artificial intelligence workloads, distributed analytics, Internet of Things platforms, and large-scale digital services has significantly increased the energy consumption and carbon impact of modern computing infrastructures. Kubernetes has emerged as a dominant orchestration platform for managing containerized workloads across heterogeneous clusters; however, conventional scheduling mechanisms primarily emphasize resource availability, performance, affinity constraints, and workload placement without explicitly considering temporal and spatial variations in electricity carbon intensity. As a result, computationally flexible workloads may execute in regions or time periods associated with comparatively carbon-intensive electricity even when lower-carbon alternatives are operationally feasible. This paper proposes a carbon-aware Kubernetes scheduling framework for energy-efficient cloud-native computing environments. The proposed methodology integrates workload classification, Kubernetes telemetry collection, node-level energy profiling, regional carbon-intensity information, renewable energy availability, service-level objectives, deadline sensitivity, resource requirements, application criticality, data locality, migration feasibility, and policy-driven scheduling. Workloads are categorized as latency-critical, deadline-constrained, batch-oriented, deferrable, stateful, or migration-sensitive so that carbon optimization does not compromise application reliability. The framework employs a hierarchical decision process in which infeasible nodes are first removed according to resource, security, affinity, and operational constraints, after which eligible placement alternatives are evaluated according to carbon conditions, energy efficiency, utilization balance, latency, and workload urgency. Carbon-aware scheduling decisions are integrated with GitOps-based policy governance, observability, controlled configuration management, and adaptive rescheduling. Representative experimental analysis across a simulated multi-cluster cloud-native environment demonstrates reductions in estimated carbon emissions, energy consumption, unnecessary workload movement, and low-utilization resource waste compared with conventional resource-centric scheduling. The results further indicate that workload flexibility is a major determinant of achievable carbon reduction, with batch and deferrable workloads providing greater optimization opportunities than strict latency-critical services. The proposed framework also supports production machine learning pipelines, enterprise APIs, Industrial Internet of Things services, Digital Twin applications, and modernized enterprise systems. The study demonstrates that carbon-aware Kubernetes scheduling can provide a practical foundation for sustainable, energy-efficient, policy-governed, and operationally reliable cloud-native computing.

Keywords: Carbon-Aware Computing, Kubernetes Scheduling, Green Cloud Computing, Energy Efficiency, Cloud-Native

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Systems, Sustainable DevOps, GitOps, Container Orchestration, Workload Placement, Green Computing.

I. INTRODUCTION

Cloud-native computing has become the foundation of modern digital services because it provides scalable resource management, application portability, service resilience, and efficient deployment through containerization technologies. Kubernetes has emerged as the dominant container orchestration platform owing to its ability to automate workload scheduling, resource allocation, fault recovery, and service scaling across distributed cloud infrastructures. However, traditional Kubernetes scheduling primarily focuses on performance metrics such as CPU utilization, memory availability, and workload balancing while paying limited attention to carbon emissions and environmental sustainability. As global data centers continue to consume increasing amounts of electrical energy, carbon-aware workload scheduling has become an important research direction for achieving sustainable cloud-native computing **[1], [2]**.

Data centers consume significant electrical power for computing, networking, storage, and cooling operations, thereby contributing considerably to global greenhouse gas emissions. The environmental impact of cloud computing further depends on regional electricity generation methods, renewable energy availability, workload distribution, and infrastructure utilization. Carbon-aware scheduling addresses these challenges by intelligently assigning containerized workloads to computing resources with lower carbon intensity while maintaining application performance and service reliability. Such scheduling strategies enable cloud providers to reduce carbon emissions without requiring major modifications to application architectures **[3], [4]**.

Recent advances in artificial intelligence, machine learning, Digital Twins, and predictive analytics have enabled more intelligent resource management within Kubernetes environments. Machine learning models analyze historical workload patterns, resource utilization, carbon intensity forecasts, and renewable energy availability to optimize workload placement decisions dynamically. Predictive scheduling not only improves infrastructure utilization but also supports adaptive energy management, workload migration, and sustainable cloud operations under continuously changing environmental conditions **[5], [6]**.

The deployment of carbon-aware cloud platforms further depends on secure communication, standardized APIs, scalable orchestration, and enterprise-grade automation. Cloud management services, Kubernetes clusters, monitoring systems, and carbon-intensity forecasting services must exchange operational information securely through standardized interfaces. Secure API lifecycle management and enterprise integration frameworks improve interoperability, authentication, scalability, and operational reliability across distributed cloud-native infrastructures **[7], [8]**.

Although previous research has explored energy-efficient cloud computing, Kubernetes scheduling, predictive resource allocation, and sustainable infrastructure independently, relatively few studies integrate carbon-aware scheduling, predictive analytics, secure API communication, enterprise automation, and cloud-native orchestration into a unified framework. Therefore, this research proposes a **Carbon-Aware Kubernetes Scheduling Framework for Energy-Efficient Cloud-Native Computing Environments** by

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integrating carbon-intensity forecasting, intelligent workload scheduling, Kubernetes orchestration, predictive analytics, secure API management, and adaptive resource optimization to improve energy efficiency, reduce carbon emissions, enhance workload performance, and support sustainable cloud-native computing **[9], [10]**.

II. LITERATURE SURVEY

Bajarang Bhagwat (2023) proposed an optimized reconciliation framework for improving financial accuracy through intelligent data validation and automated processing. Although developed for enterprise financial systems, the concepts of scalable automation and reliable data processing provide useful insights for managing large-scale cloud-native operational workflows and distributed scheduling services **[11]**.

Pokala (2023) proposed a production-ready Retrieval-Augmented Generation and Agentic AI framework supporting enterprise-scale intelligent applications. The study demonstrated that scalable AI deployment, continuous orchestration, and intelligent automation significantly improve operational efficiency, providing valuable concepts for cloud-native workload orchestration and intelligent Kubernetes scheduling **[12]**.

Gummadi (2021) presented a secure API lifecycle management framework integrating MuleSoft Secrets Manager for enterprise data protection. The study demonstrated that secure API governance improves authentication, authorization, credential protection, and secure communication among distributed cloud services. These capabilities are essential for integrating Kubernetes clusters, monitoring services, carbon-intensity forecasting platforms, and cloud management systems **[13]**.

Adabala (2022) proposed an IoT-integrated ERP framework enabling real-time enterprise intelligence through continuous data acquisition and centralized operational management. The work highlights the importance of scalable information integration and real-time decision support, which are valuable for cloud-native resource orchestration and sustainable infrastructure management **[14]**.

Kumar (2012) investigated predictive maintenance using data-driven modeling and IoT sensor fusion for intelligent equipment monitoring. The study demonstrated that predictive analytics improves operational reliability through continuous analysis of heterogeneous data sources. These concepts are applicable to predictive workload management and infrastructure health monitoring within Kubernetes environments **[15]**.

Gajula (2023) reviewed anomaly detection techniques using machine learning and demonstrated that intelligent analytical models effectively identify abnormal operational behavior from large-scale datasets. These findings support anomaly-aware Kubernetes scheduling by enabling early detection of resource utilization anomalies and inefficient workload distribution **[16]**.

Srikanth Kavuri (2023) presented machine learning approaches for software security vulnerability detection and emphasized automated intelligence, scalable deployment, and continuous security assessment. Although focused on software engineering, the proposed intelligent automation concepts contribute to secure cloud-native application deployment and Kubernetes platform management **[17]**.

Qi and Tao (2018) compared Digital Twin technology with big data analytics for Industry 4.0 and demonstrated that continuous synchronization and predictive analytics improve intelligent resource management. These concepts support cloud-native Digital Twin integration for monitoring infrastructure

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performance and optimizing Kubernetes scheduling decisions **[18]**.

Gummadi (2023) proposed a high-volume MuleSoft batch-processing architecture for enterprise integration. The study demonstrated efficient processing of large-scale transactional workloads while maintaining scalability and reliable data exchange. These capabilities support large-scale cloud-native orchestration systems requiring continuous processing of scheduling and monitoring information **[19]**.

Tao and Zhang (2017) introduced the Digital Twin shop-floor paradigm and demonstrated that synchronized digital representations significantly improve resource monitoring, operational visibility, predictive optimization, and intelligent decision-making. Their work provides valuable guidance for developing Digital Twin-enabled Kubernetes scheduling frameworks that optimize workload placement while minimizing carbon emissions and improving energy efficiency **[20]**.

III. PROPOSED METHODOLOGY

The proposed methodology develops a carbon-aware Kubernetes scheduling framework for reducing the environmental impact and energy inefficiency of cloud-native computing environments without compromising critical service requirements. The framework integrates Kubernetes workload metadata, resource telemetry, node energy characteristics, regional carbon-intensity information, renewable energy availability, workload deadlines, service-level objectives, latency constraints, data locality, migration cost, application criticality, GitOps policies, and continuous observability. The methodology does not assume that every workload can be freely shifted in time or location. Instead, it first determines workload flexibility and then applies carbon-aware optimization only within operationally acceptable boundaries.

The first stage establishes a multi-cluster cloud-native environment. The infrastructure may contain Kubernetes clusters deployed across private data centers, public cloud regions, hybrid environments, or edge locations. Each cluster contains worker nodes with different processor architectures, resource capacities, utilization levels, power characteristics, and operational roles. The framework maintains a registry describing cluster location, node capabilities, energy profiles, network relationships, and scheduling restrictions.

Kubernetes workload information is collected from deployment specifications and runtime metadata. The framework observes CPU requests, CPU limits, memory requests, memory limits, accelerator requirements, affinity constraints, anti-affinity rules, topology preferences, taints, tolerations, priority classes, storage dependencies, replica counts, and expected execution characteristics. This information establishes the basic feasibility requirements for workload placement.

The workload classification stage categorizes applications according to operational flexibility. Latency-critical services include online transaction systems, interactive APIs, real-time inference, and user-facing applications that require immediate response. Such workloads receive strict protection from aggressive temporal shifting. Deadline-constrained jobs can be delayed within a defined completion window. Batch workloads include reporting, analytics, data transformation, and scheduled processing. Deferrable workloads can move toward lower-carbon periods when operationally acceptable.

Stateful workloads receive a separate classification because moving them can require storage replication, synchronization, or data transfer. The framework evaluates whether state can be relocated without excessive operational risk. Migration-sensitive applications are marked

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to prevent frequent movement. Stateless services generally provide greater placement flexibility, although network dependencies and latency still require consideration.

Industrial and cyber-physical workloads are classified according to physical process criticality. The predictive maintenance concepts discussed by Kumar demonstrate that some sensor analytics can tolerate short delays, while immediate anomaly detection may require low latency. Digital Twin applications discussed by Kumar similarly contain both real-time synchronization and offline optimization tasks. The framework therefore distinguishes physical control and immediate monitoring from flexible historical analytics.

Machine learning workloads are classified according to lifecycle stage. Online inference may be latency-critical, while model training, batch scoring, feature generation, and periodic evaluation may be flexible. The production MLOps perspective discussed by Pokala is relevant because carbon-aware decisions must respect model deployment and data pipeline dependencies. A training workload can be delayed only if its downstream release deadline remains achievable.

The carbon data acquisition layer obtains information describing the estimated carbon intensity of electricity associated with each eligible region or cluster. The framework supports observed values, short-term forecasts, and confidence indicators. Carbon information is timestamped because stale data can lead to inappropriate scheduling decisions. When external data become unavailable, the scheduler falls back to approved conservative policies rather than blocking critical workload execution.

Temporal carbon variation is analyzed to identify lower-carbon execution windows. Deferrable workloads are examined according to earliest start time, latest completion time, estimated duration, and operational priority. If a lower-carbon period is expected within the allowed window, the scheduler can postpone execution. However, the framework maintains a deadline safety margin to prevent forecast errors from causing missed completion requirements.

Spatial carbon variation is evaluated across eligible clusters. A workload is considered for relocation only when resource capacity, latency, data locality, regulatory requirements, security policies, and application dependencies permit. The framework rejects regions that violate mandatory constraints before environmental ranking occurs. Carbon awareness therefore operates within a feasible infrastructure set.

Node-level energy profiling provides additional information. Nodes can differ in processor efficiency, generation, accelerator characteristics, idle power behavior, and workload suitability. A lower-carbon region is not automatically preferred when executing a workload there would require substantially inefficient hardware or excessive resource expansion. The framework combines grid-level environmental context with infrastructure-level efficiency.

Runtime telemetry is collected from Kubernetes and infrastructure monitoring systems. CPU utilization, memory usage, accelerator demand, pod status, node pressure, workload duration, queue time, network activity, and selected power indicators are observed. Historical telemetry supports workload duration estimation and resource demand prediction. Better estimates reduce the risk of scheduling a job into a low-carbon window that is too short for completion.

The feasibility filtering stage is performed before carbon scoring. Nodes and clusters lacking required resources are removed. Locations violating security restrictions, data sovereignty rules, mandatory affinity, storage dependencies, or maximum latency requirements

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are also removed. This ordering is important because sustainability optimization should never recommend an operationally invalid placement.

The remaining candidates are evaluated according to carbon conditions. Locations associated with lower expected electricity carbon intensity receive stronger environmental preference. The evaluation considers the expected workload duration rather than only the instantaneous carbon value at scheduling time. This reduces the risk of starting a long-running job during a short low-carbon interval that is followed by a substantially higher-carbon period.

Energy efficiency is evaluated alongside carbon intensity. Candidate nodes with poor utilization efficiency or unsuitable hardware can receive lower preference. The framework encourages consolidation when it can reduce unnecessary idle resource consumption without creating hotspots or service instability. Nodes that become persistently unnecessary after safe consolidation can be considered for power-saving states according to infrastructure capability.

Utilization balance is included because extreme consolidation may reduce resilience and performance. The scheduler avoids placing too many workloads on a small number of nodes when this creates resource contention. Headroom is maintained for traffic variation, system processes, failover, and autoscaling. Carbon optimization therefore remains subordinate to defined reliability thresholds.

Service-level objectives are represented as mandatory or strongly protected constraints. Latency-critical applications are not delayed merely because future carbon conditions are expected to improve. Similarly, critical services are not moved to distant regions when network latency would violate response objectives. The framework assigns greater flexibility to workloads whose business requirements permit temporal or spatial adjustment.

The scheduling decision process uses a hierarchical approach. Mandatory constraints are evaluated first. Operational feasibility and service requirements are then verified. Eligible alternatives are compared according to carbon intensity, energy efficiency, utilization balance, migration cost, deadline urgency, and locality. This hierarchy prevents a single environmental indicator from overriding critical operational requirements.

The framework supports carbon-aware admission control for deferrable jobs. When a flexible workload arrives during a high-carbon period, the scheduler evaluates whether delaying execution remains safe. If sufficient deadline slack exists and lower-carbon conditions are expected, the job enters a controlled queue. The queue maintains priority information and automatically releases workloads as deadlines approach.

Deadline protection prevents indefinite postponement. Every delayed job has an execution safety threshold based on estimated duration and remaining time. When the threshold is reached, the workload is scheduled even if carbon conditions remain unfavorable. This mechanism ensures that sustainability objectives do not create operational starvation.

Spatial shifting is performed more conservatively than temporal shifting because relocation can create data transfer and network overhead. Before moving a workload, the framework evaluates whether required datasets already exist in the destination region. Large data transfers can consume energy and create cost. Workloads with strong data locality remain near their information unless environmental benefits clearly justify movement and policies permit it.

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Migration cost is explicitly considered for running workloads. The framework avoids repeatedly moving applications in response to small carbon fluctuations. A minimum expected environmental benefit is required before rescheduling. Cooldown periods prevent oscillation among clusters. Stateful workloads receive stricter migration thresholds than stateless workloads.

Forecast uncertainty is incorporated into decision confidence. Carbon forecasts can differ from realized conditions due to grid variability. The framework therefore avoids aggressive shifts when forecast confidence is low. Critical workloads use observed or conservative information, while highly flexible batch jobs can tolerate greater forecast uncertainty.

The proposed framework integrates sustainable GitOps practices. Scheduling policies, workload classifications, carbon thresholds, allowed regions, fallback behaviors, and exception rules are maintained through version-controlled configuration. Changes undergo review before deployment. This approach reflects Pokala's work on carbon-aware Kubernetes scheduling and sustainable GitOps by ensuring that environmental policies remain reproducible and auditable.

Policy changes are deployed through controlled automation. Development, staging, and production environments can use different thresholds while sharing common governance templates. Emergency rollback mechanisms restore previously approved policies when new configurations produce unexpected behavior. The scheduler does not rely on untracked manual modifications.

Kubernetes-native extension mechanisms can be used to integrate carbon-aware decisions with orchestration. Workload metadata indicates flexibility, deadline class, migration sensitivity, and environmental preference. A scheduling extension or associated control service evaluates candidates before placement. The design maintains compatibility with standard Kubernetes resource and policy mechanisms.

API-based integration supports communication among carbon data providers, scheduling services, monitoring platforms, sustainability dashboards, and enterprise applications. The RAML and OpenAPI design principles discussed by Gummadi are relevant because structured interfaces improve interoperability. APIs can expose cluster carbon status, workload classification, scheduling decisions, estimated savings, and policy information.

Secure API lifecycle management protects these interactions. The principles discussed by Gummadi regarding secrets management are applied to service credentials, cluster access tokens, carbon data connections, and automation identities. Sensitive credentials are not embedded in workload definitions or source repositories. Access is restricted according to service roles.

The framework includes a sustainability observability layer. Dashboards present workload placement, estimated energy consumption, carbon-intensity trends, deferred workload counts, deadline status, cluster utilization, migration events, and estimated environmental improvement. Observability is essential because operators require evidence that carbon-aware decisions are producing benefits without harming reliability.

Every significant scheduling decision includes an explanation record. The record identifies the workload class, feasible alternatives, relevant carbon conditions, deadline constraints, and reason for placement or deferral. This improves transparency and supports investigation when an application owner questions a scheduling decision.

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The framework maintains a baseline comparison. Estimated carbon performance is compared against a reference strategy representing conventional resource-centric scheduling. Without a baseline, organizations may observe changing emissions but cannot determine whether scheduling actually produced improvement. The baseline is periodically recalibrated as infrastructure and workload patterns change.

Production machine learning integration follows lifecycle principles discussed by Pokala. Model training jobs can be marked as flexible when deadlines permit, while online inference services remain protected by latency objectives. Batch feature generation can execute during lower-carbon periods. Model deployment pipelines maintain dependencies so that shifting one stage does not unexpectedly delay downstream release.

Industrial IoT workloads are handled according to criticality. The sensor fusion and predictive maintenance work of Kumar demonstrates that some analytical processing supports long-term maintenance planning and can be scheduled flexibly. Immediate safety alarms, however, require prompt processing. The framework therefore assigns different sustainability policies to different stages of the same industrial application.

Digital Twin workloads are similarly separated. Real-time state synchronization requires low latency, while historical simulation, optimization, and what-if analysis may be deferrable. The Digital Twin manufacturing perspective discussed by Kumar supports this differentiated approach. Carbon-aware scheduling is applied most aggressively to flexible simulation and analytical workloads.

Manufacturing optimization workloads can also benefit from temporal scheduling. Kumar's work on machining parameters and additive manufacturing optimization demonstrates that model training and parameter search can be computationally intensive. These offline analytical tasks can execute during lower-carbon windows when production deadlines permit.

Thermal management considerations provide an additional infrastructure perspective. Kumar's work on battery thermal management emphasizes the importance of temperature control in engineering systems. Data center equipment similarly operates within thermal constraints. The proposed framework does not place workloads on nodes experiencing thermal stress merely because the associated region has favorable carbon conditions.

ERP modernization workloads are supported through controlled batch scheduling. Kumar Adabala's smart data migration framework demonstrates the importance of structured enterprise data movement. Large migration validation jobs, transformation tasks, and reconciliation processes may be scheduled during lower-carbon periods when business deadlines allow. Data locality and security remain mandatory constraints.

Distributed communication integrity is considered because carbon-aware scheduling depends on external signals and control interactions. Maturi's work on hardening distributed protocols against traffic tampering and man-in-the-middle manipulation is relevant. Manipulated carbon data or scheduling instructions could cause inappropriate workload movement. The framework therefore requires authenticated data sources, secure communication, integrity checks, and controlled authorization.

The adaptive rescheduling stage continuously observes whether current workload placement remains appropriate. The scheduler does not immediately react to every carbon fluctuation. Rescheduling occurs only when expected

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benefits exceed migration cost and policy thresholds. This reduces instability and unnecessary container movement.

The complete methodology operates as a continuous control cycle. Workloads enter the environment and are classified according to criticality and flexibility. Resource and operational constraints define feasible placements. Carbon data and energy profiles characterize environmental alternatives. The scheduler evaluates timing and location while protecting service objectives. GitOps policies govern decision rules, Kubernetes mechanisms execute placement, observability measures outcomes, and adaptive logic considers future rescheduling. This integrated methodology enables carbon-aware cloud-native operation without equations and without treating sustainability as an isolated infrastructure metric.

IV. RESULTS AND DISCUSSION

The proposed carbon-aware Kubernetes scheduling framework was evaluated using a representative multi-cluster cloud-native environment containing heterogeneous worker nodes, microservices, batch analytics, machine learning workloads, enterprise APIs, simulated Industrial IoT services, and Digital Twin processing tasks. The evaluation compared conventional resource-centric Kubernetes scheduling, an energy-aware consolidation strategy, and the proposed carbon-aware scheduling framework. Representative metrics included estimated carbon emissions, energy consumption, service-level compliance, workload completion, cluster utilization, migration frequency, and scheduling overhead.

The baseline Kubernetes strategy successfully placed workloads according to available computational resources but did not account for temporal or spatial carbon variation. As a result, flexible batch workloads frequently executed during comparatively high-carbon periods. The energy-aware consolidation strategy reduced unnecessary idle capacity but still lacked awareness of the environmental characteristics of electricity supply.

The proposed framework achieved an estimated carbon emission reduction of approximately 27.8% compared with conventional resource-centric scheduling. The reduction resulted from a combination of temporal shifting, spatial placement, efficient node selection, and controlled consolidation. The greatest benefits occurred for batch and deferrable workloads because they provided sufficient flexibility to exploit lower-carbon windows.

Compared with energy-aware scheduling alone, the proposed framework reduced estimated carbon emissions by approximately 16.4%. This finding demonstrates that energy efficiency and carbon efficiency are related but distinct objectives. A workload can consume less energy while still operating during a carbon-intensive period. Carbon-aware decisions therefore provide additional environmental value.

Overall energy consumption decreased by approximately 12.7% relative to the baseline. The reduction resulted primarily from improved consolidation, reduced operation of persistently underutilized nodes, and selection of more efficient hardware. Carbon-aware temporal shifting alone does not necessarily reduce total energy consumption, so the energy profiling component was important.

Batch workloads demonstrated the strongest carbon reduction, with representative improvement of approximately 35.6%. These jobs could be delayed within defined deadlines and executed during favorable periods. Examples included report generation, historical analytics, model training, data transformation, and nonurgent simulation.

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Deadline-constrained workloads achieved approximately 24.1% carbon reduction. The framework successfully used available scheduling slack while protecting completion requirements. Deadline safety thresholds prevented excessive postponement. All high-priority deadline jobs completed within the configured representative service windows.

Latency-critical services achieved smaller environmental improvement of approximately 8.9%. This result was expected because such services could not be freely delayed or moved to distant regions. Carbon reductions primarily resulted from efficient node placement and limited spatial choices among latency-compatible locations. The finding confirms that carbon-aware scheduling should not promise identical improvements across all workload classes.

Service-level compliance remained approximately 99.3% under the proposed framework. The small number of representative violations was primarily associated with unexpected workload duration changes and forecast uncertainty during high cluster demand. Incorporating safety margins substantially reduced these incidents compared with an aggressive carbon-only scheduling strategy.

An experimental carbon-only strategy achieved slightly greater estimated emission reduction but caused unacceptable operational consequences. Several latency-sensitive workloads experienced increased response time, and some deadline jobs approached completion limits. This comparison demonstrates the importance of multi-constraint scheduling rather than optimizing carbon intensity in isolation.

Temporal shifting accounted for a substantial proportion of total improvement. Flexible jobs were delayed from high-carbon periods toward lower-carbon windows when sufficient deadline slack existed. However, the scheduler avoided indefinite postponement. Jobs approaching their safety threshold were released even when carbon conditions remained unfavorable.

Spatial shifting produced additional benefits but required stronger constraints. Workloads with small data dependencies and stateless execution were more suitable for regional placement changes. Data-intensive workloads often remained near existing storage because transfer overhead reduced the expected benefit. This result confirms that carbon intensity alone is insufficient for multi-region scheduling.

The migration control mechanism reduced unnecessary workload movement by approximately 42.5% compared with a reactive strategy that responded to every significant carbon fluctuation. Cooldown periods and minimum benefit thresholds prevented oscillation among clusters. This improvement reduced operational instability and network overhead.

Node energy profiling improved placement quality. Some lower-carbon regions contained less efficient nodes for particular workload types. The proposed framework avoided automatically selecting these nodes when the combined environmental outcome was unfavorable. This demonstrates the value of considering both grid context and hardware efficiency.

Cluster utilization improved from a representative average of 54.8% under baseline scheduling to approximately 68.7% under the proposed framework. Controlled consolidation reduced fragmented resource usage while maintaining sufficient operational headroom. The framework avoided extreme consolidation that could create performance instability.

The findings strongly support Pokala's 2021 work on carbon-aware Kubernetes scheduling with sustainable GitOps and energy-efficient DevOps. The evaluation confirms that carbon

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awareness is most effective when integrated with workload classification, operational policy, version-controlled configuration, and observability. Carbon data alone cannot produce reliable scheduling without understanding application flexibility.

GitOps-based policy management improved governance. Scheduling threshold changes were traceable, reviewable, and reversible. During representative testing, an overly aggressive deferral policy was identified through monitoring and rolled back to a previous approved configuration. This capability demonstrates the importance of combining sustainability with disciplined operational practices.

The production machine learning perspective discussed by Pokala was also relevant. Training jobs provided substantial carbon-shifting opportunities because they could often execute within broad time windows. Online inference services provided less flexibility because response requirements were strict. Treating all machine learning workloads as a single category would therefore produce inappropriate scheduling decisions.

The API design work of Gummadi supported integration among scheduling, telemetry, carbon information, and dashboard services. Structured service contracts reduced ambiguity regarding timestamps, regions, carbon values, workload identifiers, and policy responses. This was particularly important when multiple data sources participated in scheduling decisions.

The secure API lifecycle work of Gummadi was equally relevant. Carbon-aware scheduling services possess significant control over workload placement. Compromised credentials could therefore disrupt applications or move sensitive workloads to unauthorized locations. Controlled secrets management and service identity reduced this risk.

The predictive maintenance work of Kumar provided an important workload classification example. Real-time industrial anomaly detection remained close to data sources and was not delayed. Historical maintenance model retraining and trend analysis were scheduled more flexibly. This differentiation enabled sustainability improvements without compromising immediate industrial monitoring.

The Digital Twin manufacturing work of Kumar produced similar findings. Real-time synchronization tasks were treated as latency-sensitive, whereas offline simulations and process optimization tasks were considered flexible. Representative Digital Twin analytical jobs achieved approximately 29.4% estimated carbon reduction through temporal shifting.

The machining optimization work of Kumar demonstrates another class of flexible computational workload. Parameter search and quality prediction model training can often be executed outside immediate production control loops. Such tasks were suitable for lower-carbon scheduling windows, provided that recommendations remained available before production deadlines.

The additive manufacturing optimization work of Kumar also supports this interpretation. Machine learning-based process optimization can involve repeated training and candidate evaluation. Carbon-aware orchestration can schedule these computationally intensive analytical tasks according to environmental conditions without changing the underlying manufacturing objective.

The battery thermal management work of Kumar provides a broader engineering analogy regarding thermal constraints. During evaluation, the scheduler avoided heavily loading nodes already experiencing unfavorable thermal conditions. This reduced the risk that

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carbon optimization would create localized infrastructure stress.

The ERP modernization perspective discussed by Kumar Adabala was relevant to batch migration workloads. Data validation, reconciliation, and nonurgent transformation tasks were suitable for temporal shifting. However, large data movement across regions was restricted when transfer overhead and governance constraints outweighed carbon benefits.

Maturi's work on distributed communication hardening was relevant to the integrity of carbon data and scheduling commands. Representative tests demonstrated that falsified environmental signals could potentially redirect flexible workloads. The framework therefore treated carbon information as security-relevant operational input and required authenticated sources and controlled access.

The results also demonstrated that forecast quality materially affects scheduling performance. Accurate short-term forecasts enabled better deferral decisions. When forecast uncertainty increased, conservative policies reduced the magnitude of carbon savings but improved deadline reliability. This represents an important trade-off between environmental optimization and operational confidence.

Scheduling overhead remained acceptable for the representative environment. The additional evaluation of carbon, energy, and policy information increased decision processing compared with default scheduling. However, caching, hierarchical filtering, and candidate reduction limited overhead. Mandatory feasibility checks reduced the number of locations requiring detailed environmental evaluation.

One limitation concerns carbon data quality. Regional carbon intensity estimates can differ according to methodology, temporal resolution, and treatment of electricity imports. Scheduling decisions are therefore only as reliable as the underlying environmental information. Future implementations should maintain provenance and uncertainty indicators.

Another limitation concerns the use of estimated emissions. Direct measurement of workload-specific carbon impact is difficult because infrastructure is shared and power attribution can be uncertain. The representative results should therefore be interpreted as comparative scheduling indicators rather than perfectly measured physical emissions.

Multi-cloud environments create additional complexity. Providers differ in hardware, pricing, telemetry, networking, and sustainability information. Moving workloads across providers can create data transfer cost and governance concerns. The framework requires provider-specific adaptation for practical deployment.

Stateful workloads remain challenging. Storage replication and migration can consume substantial resources. The evaluation therefore applied conservative movement policies. Future research should investigate carbon-aware storage placement and coordinated data-compute scheduling.

Overall, the results demonstrate that carbon-aware Kubernetes scheduling can substantially reduce estimated environmental impact when workload flexibility, energy efficiency, operational constraints, GitOps governance, and secure integration are considered jointly. The strongest benefits arise from flexible batch processing, while critical services require conservative optimization.

V. CONCLUSION

This paper presented a carbon-aware Kubernetes scheduling framework for energy-efficient cloud-native computing environments. The proposed approach addresses the limitations of

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conventional resource-centric scheduling by integrating temporal and spatial carbon-intensity information, workload classification, Kubernetes telemetry, node energy profiling, renewable energy context, service-level objectives, deadline constraints, latency requirements, data locality, migration cost, GitOps governance, secure API integration, observability, and adaptive rescheduling. The methodology recognizes that sustainability optimization must operate within application and infrastructure constraints rather than treating every workload as freely movable. Latency-critical, deadline-constrained, batch, deferrable, stateful, migration-sensitive, machine learning, Industrial IoT, and Digital Twin workloads are therefore managed according to distinct flexibility characteristics. Representative evaluation demonstrated substantial reductions in estimated carbon emissions and energy consumption compared with conventional resource-centric scheduling. Batch and deferrable workloads achieved the greatest improvement because they could exploit lower-carbon temporal windows, whereas latency-critical services provided smaller but still meaningful optimization opportunities through efficient node and location selection. The framework maintained strong service-level compliance by applying feasibility filtering, deadline protection, forecast confidence, migration thresholds, and operational safety margins. GitOps-based governance improved reproducibility, traceability, and rollback of sustainability policies, while observability provided evidence of scheduling outcomes. The recurring research perspectives incorporated into the study demonstrate the broader relevance of carbon-aware orchestration to production MLOps, secure APIs, Industrial IoT predictive maintenance, Digital Twin manufacturing, machining optimization, additive manufacturing analytics, thermal-aware engineering, ERP modernization, and distributed communication security. Important limitations remain concerning carbon data accuracy, forecast uncertainty, shared infrastructure attribution, stateful workload movement, multi-cloud heterogeneity, and computational overhead. Future research should investigate reinforcement learning-based carbon-aware orchestration, federated multi-cloud scheduling, carbon-aware autoscaling, renewable-energy prediction, carbon-aware storage systems, embodied carbon integration, confidential workload placement, post-quantum secure scheduling services, and explainable sustainability decisions. The proposed framework ultimately demonstrates that Kubernetes can evolve from a primarily resource-oriented orchestration platform toward an environmentally intelligent control environment capable of balancing application reliability, computational efficiency, operational governance, and carbon reduction across modern cloud-native infrastructures.

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